An Internet of Things (IoT) Management System for Improving Homecare - A Case Study

Areej Almazroa, and Hongjian Sun

***Abstract*—Due to the massive increase of the population, the number of hospital visits by patients are increasing which puts a pressure on hospitals. Nowadays, the need for taking care of patients while they are at home is essential. Internet of Things (IoT) has been widely used in different areas such as healthcare and smart homes. IoT will assist in minimizing the hospital burden of frequent patients' visits. Applying IoT in healthcare will improve the efficiency and effectiveness, bring economic benefits, and reduce human exertions. It is well known that the best health monitoring system is able to detect abnormalities and able to make diagnosis without human exertion. However, this kind of system is dealing with health conditions which are essential and sensitive that require high range of accuracy to be reliable. This paper presents an Electrocardiogram (ECG) monitoring framework that overcome the accuracy limitation. Signal processing and feature extraction are applied. For the diagnosis purpose a classification stage is made in two ways; threshold values and machine learning to increase the accuracy. Experiment results reveal that the proposed model is accurate in the diagnosis of heart diseases more than other researches which makes it more confident to rely on from health experts point of view.**

***Index Terms*—Internet of Things (IoT), homecare, healthcare, emergency assistant, Electrocardiogram (ECG).**

I. Introduction

Due to the ageing population and the increasing number of patients in hospitals, homecare management systems are increasingly important. Integrating these systems with IoT technologies will provide more homecare functions. Using IoT sensors and actuators inside the home with the assist of communication technologies will help caregivers monitor their patients remotely. Moreover, to reduce the burden on caregivers several decision making can be applied based on the sensor data. Providing reliable and comfort living along with accurate health caring is the main objective of this paper.

With the innovation of IoT, providing a good life for people in smart cities is one of the important aspects of daily life. Nowadays, healthcare monitoring systems inside homes become a focus of many researches. An IoT mobile healthcare system inside home for disabled users who used wheelchair was investigated in [1]. The architecture and design of the system was proposed using Wireless Body Area Network (WBAN). The WBAN nodes contains; heart rate and ECG sensors, pressure detecting cushion, temperature sensor, humidity sensor and control actuators. The user wears a watch at wrist to monitor heart rate with ECG and the sink node located at the belt. The wheelchair holds the pressure cushion which is used to detect whether the user falling from the wheelchair or not and the accelerator sensor that is used to detect the falling of the wheelchair itself. The architecture of the system contains three layers. The WBANs and smart objects layer, the smart phone layer, and the data centre layer in the cloud. The communication protocols used were Zigbee and Bluetooth. The smart phone was used as a gateway and a server. This system satisfies the mobility of data collection, healthcare monitoring based on the environment and remote interaction with surroundings. In addition, Sung and Chang [2] implemented an Android IoT healthcare system platform. This system uses cloud computing to perform storage, processing, collection and analysis of data. In this research, vital sign data processing fusion algorithms and evidence theory were used. The system was focused on measuring blood pressure, ECG, oxygen saturation, respiration rate and body temperature through Bluetooth communication using portable device. The vital signs were transmitted to the Android mobile phone using WiFi and Bluetooth modules then uploaded to the cloud to be downloaded by caregivers for monitoring. In advance, this system sends SMS notification to caregivers once the data is ready in the cloud and also provides video chat with caretakers if needed.

Smart health emergency systems in homes with alarming and warning track the attention of many researches. One of these researches proposed a wearable health monitoring system for sensing temperature and heart beat rate for babies in realtime using smart phone [3]. The system can issue health status report and notify in case of emergency situations. It consists of wearable hardware device, middle-ware, cloud server and smart phone application. By using hand glove, the system monitored temperature from the wrist line and heart rate from tip of finger. The system used Arduino that can act as a micro-controller between body sensors and middle-ware. The communication protocol used in this system was Bluetooth. The battery used in hand glove was coin cell. Raspberry Pi used as a middle-ware device with WiFi and Bluetooth interface that can transfer vital sign data to the cloud server for processing using Microsoft Azure platform in addition to storing them in the local storage. The application was built on .net platform using C# programming language and Windows phone device. In addition the system sent notification and alarms using the mobile application based on realtime monitoring.

Heart is one of the most important organ in human body

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that requires monitoring and caring. Any issue with that organ may terminates the human life. ECG home monitoring systems were rarely used due to the limitation in the accuracy. Yang *et al.* [4] proposed an IoT wearable ECG monitoring system. In this system, a new ECG monitoring method using IoT and cloud techniques was demonstrated. The ECG data collected using wearable sensors and sent to the cloud using WiFi communication to visualize and store data for future analysis. Hyper Text Transfer Protocol (HTTP) and Message Queuing Telemetry Transport (MQTT) protocols were used in the cloud for giving ECG data to users in a short time and anywhere using a web-based GUI. The system was evaluated in terms of reliability using a healthy body volunteer person. The system was reliable for realtime ECG data in terms of collecting and displaying. Another IoT monitoring framework was proposed in [5]. ECG and other biomedical data were gathered by sensors to be sent using Bluetooth technology to the cloud for accessibility. Several signal processing techniques were used for ECG signals. Watermarking used to enhance the security in the client side before send it to the cloud.Spectral and temporal features were extracted in the cloud and then classified using Support Vector Machine (SVM) machine learning classifier. The classification result was sent to health experts then the final decision sent to the cloud to notify the patient. Experimental evaluation and simulation were used for system validation. The simulation was applied by installing IoT ECG monitoring service in the cloud. The accuracy for the classification was 83% which is still low and need to be increased. Moreover, Mahdy *et al.* [6] presented an IoT ECG holter device for Arrhythmia detection with alarming. An ECG sensor was used to take the real time ECG signals from the patient's chest and send it to the Android smart phone through Bluetooth module. K-Nearest Neighbors (KNN) machine learning algorithm was used for classifying the ECG signals to normal and abnormal. The classification accuracy was 70% for normal cases and 69% for abnormal on 303 patients. The accuracy is still low to rely on the system.

Our aim is to design an IoT homecare management system by remote monitoring of patients and elderly to provide best diagnosis and comfort living in accurate manner. The proposed model will make feature extraction and classification for the diagnosis purpose using fixed threshold values and one of the machine learning algorithm. Applying machine learning algorithm will increase the accuracy of the system to be reliable inside homes for best remote diagnosis.

This paper makes two significant contribution to the field of home caring:

- Design an ECG monitoring model for the diagnosis of ECG signals that based on feature extraction and classification stages.
- Apply one of the machine learning algorithm in the classification stage to increase the accuracy of ECG diagnosis.

The paper organised as follows: in section II, we provide a detailed description of the proposed model and the processes made in each stage. In section III we present the simulation setup parameters and discuss the simulation results.

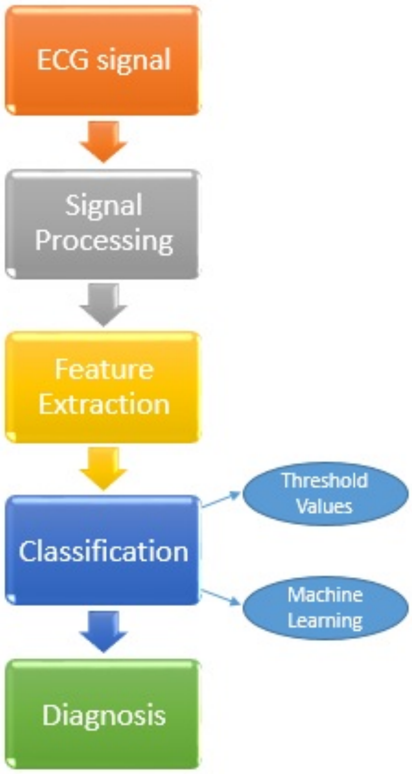


Fig. 1: Model Processes

II. Proposed Model

We will consider an IoT ECG monitoring system where currently few researches provided. All of these researches missing accuracy, reliability and data validation. First contribution, we will propose an ECG monitoring framework for feature extraction and classification on online database. Second, we will apply machine learning algorithm to increase the accuracy. Fig. 1 summarize the main model processes of our work.
We will focus on the following points:

- Implement an ECG monitoring model.
- Download an online database of ECG signals and save them in the local storage.
- Apply signal processing techniques on the ECG signal.
- Extract features from ECG signal.
- Classify the ECG signal using one of the machine learning algorithm to increase the accuracy.

A. *ECG Signal*

Each ECG signal has a standard shape which contains of five main waves as shown in Fig. 2:

- P wave (Q-pre): the atrial systole contraction pulse.
- Q wave: the downward deflection immediately preceding the ventricular contraction.
- R wave: the peak of the ventricular contraction.
- S wave: the downward deflection immediately after the ventricular contraction.
- T wave (S-post): the recovery of the ventricles.

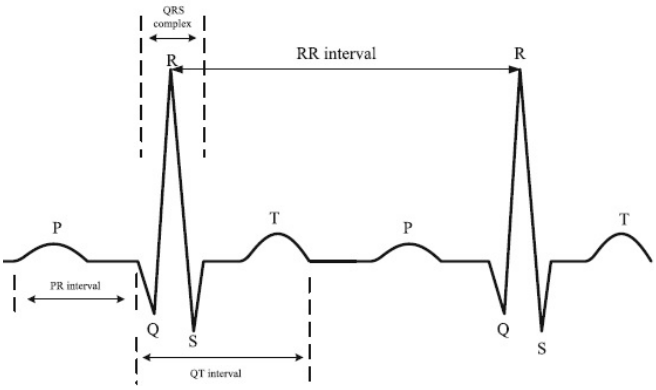


Fig. 2: ECG signal components

B. Signal Processing

Signal enhancement techniques are required for ECG signals to reduce the noise. This preprocessing step is critical for accurately finding the waves in the ECG signal that is very important in the monitoring and diagnosing. Two techniques are used in our model:

1) Low Pass Filter: A low pass filter is a signal enhancement technique to reduce the noise by reducing high frequency components from the signal to produce it much clearer. Also, it is used to remove external interference from the signal to avoid artifacts. However, the inappropriate using of that filter may lead to misdiagnosis. Low pass filter is worked by putting the signal in lower frequency then attenuate the signal with higher frequency.

2) Savitzky Golay filter: A Savitzky Golay filter is a digital filter that is used for scaling the signal, smoothing and differentiation. This filter is applied by using least squares technique. It is applied to increase the signal to noise ratio without distorting the signal. The signal after that filter becomes much clearer and wider.

C. Feature Extraction

After the signal processing stage, the signal is clean and clear. The peaks and waves can be marked. The interval between the ECG waves are so important in the diagnosis purposes. Several features can be extracted using the waves and peaks of ECG signal. The specification of those features are [7]:

- QRS Complex: the time interval between Q and S waves in milliseconds.
- RR interval: the time interval between two adjacent R waves in milliseconds.
- Heart Rate: calculated by dividing 60 over the RR interval in beat per minute as expressed by eq. 1.

$$HR(bpm) = \frac{60}{RRinterval} \quad (1)$$

- QT interval: the time interval between the start of Q wave and the end of S wave in milliseconds.
- Corrected QTc interval: the QT interval normalized by the square root of RR interval in milliseconds as expressed by eq. 2. (Bazett formula)[8].

$$QTc = \frac{QT}{\sqrt{RRinterval}} \quad (2)$$

The normal ranges for each feature can be found in table I[4].

TABLE I: ECG features threshold values.

ECG Feature	threshold value
QRS	$<$ 120 ms
RR interval	600-1000 ms
QT interval	320-440 ms
Hear Rate	40-105 bpm

D. Classification & Diagnosis

The classification and diagnosis of our model are made in two ways:

1) Threshold values: Several diseases can be figured out from the feature extraction step using the threshold values method. If the feature value goes beyond or above the threshold value, a disease can be discovered as shown in table II[5].

2) Machine Learning: Machine learning algorithms can be used to increase the accuracy of the diagnosis and to reduce human exertions. It is the field of artificial intelligence that gives the computer the ability to learn from data to make decisions without being fixed programmed. SVM is one of the most used linear supervised machine learning algorithm for best classifying the data using a segregate hyperplane. For ECG classification and based on the literature, SVM produced much better than other machine learning algorithms.

III. Experiment Results

A. Simulation Set up

For experiment results, 48 ECG signals were taken from MIT-BIH database [9]. Each signal is made up of half an hour recording from Arrhythmia Laboratory [10], [11]. Those signals were taken from a collection of mixed people 60% inpatient and 40% outpatient between 1975 and 1979. The signals were digitized at 360 samples per second per channel. A simulation model is built using MATLAB environment R2018a on Intel Core i7 processor built in a desktop personal computer. The ECG signals are downloaded from the database then passed through the simulation.

B. Simulation Results

First, we have plotted each signal as shown in Fig. 3 to show the waves of the signal. The plot is made in samples per amplitude. The signal of this patient contains 3600 samples. This signal contains a repeatedly basic signal described in Fig. 2 that contains all the components. However, some noise are recognised that requires the need for some signal enhancement techniques. For that reason, two signal processing techniques were applied. A low pass filter was implemented to reduce

TABLE II: Diseases discovered from abnormal ECG feature values.

ECG Feature	Abnormal value	Disease
QRS	> 120	Disruption of the heart's conduction system, or severe Hyperkalaemia
RR interval	< 120	Wolff Parkinson White syndrome
	> 200	First degree of Atrioventricular block
QTc	> 440	Ventricular Tachyarrhythmia
Hear Rate	< 40 or > 105	Abnormal Heart Beat

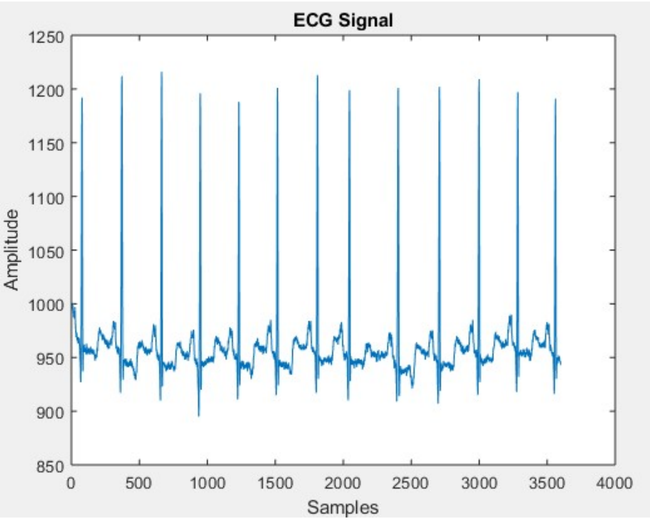
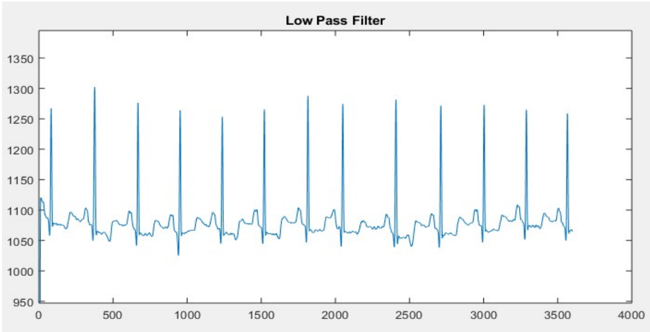
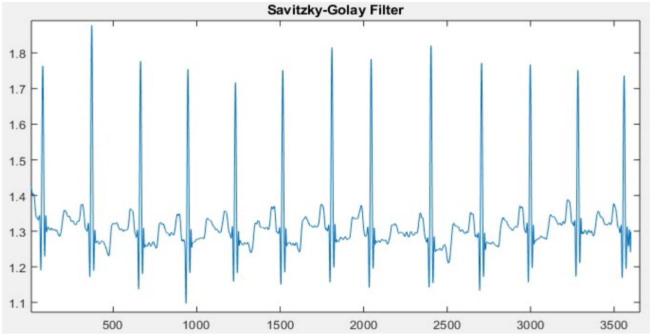


Fig. 3: ECG signal of the first patient



(a) Low-Pass filter



(b) Savitzky-Golay filter

Fig. 4: Signal Processing

the noise of the signal as shown in Fig. 4a. The edges of the signal are clearly configured and the noise are removed.

Before extracting the feature, the signal need to be scaled. A Savitzky Golay filter is implemented as shown in Fig. 4b. The small details of the movement can be seen clearly and it is ready now for the feature extraction step.

In the feature extraction method, five main waves are found Q, R, S, P and T waves. Those waves and peaks are marked as shown in Fig. 5. P peaks represent the highest peak in red triangle, where Q peaks represent the bottom one in green squares. The other peaks are marked based on the beginning of each wave.

Several features are extracted using the waves and peaks marked. The values of the features for the first patient are:

- QRS= 38.00 ms
- Heart rate= 101.01 beat/min
- RR interval= 594.00 ms
- QT interval= 237.60 ms
- QTc interval= 308.29 ms

All these features are stored in the local database to apply classification methods on them.

For the classification step based on the threshold value strategy, a warning message is shown with the diagnosis specified. For the first patient case, the warning message was: *This patient may have first degree of Atrioventricular Block.*

Several other diagnosis messages are displayed based on the feature values:

- This patient may have: Abnormal Heart Beats.
- This patient may have: Wolff Parkinson White syndrome.
- This patient may have: A disruption of the hearts conduction system, or severe Hyperkalemia.
- This patient may have: Ventricular Tachyarrhythmia.

Several machine learning classification methods were applied in our model. By using classification learner tool in Matlab, SVM was selected as the best classification method

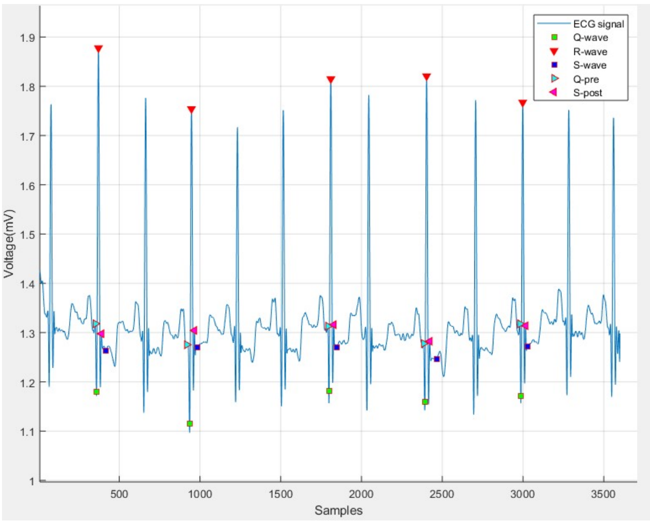


Fig. 5: ECG Signal Peaks

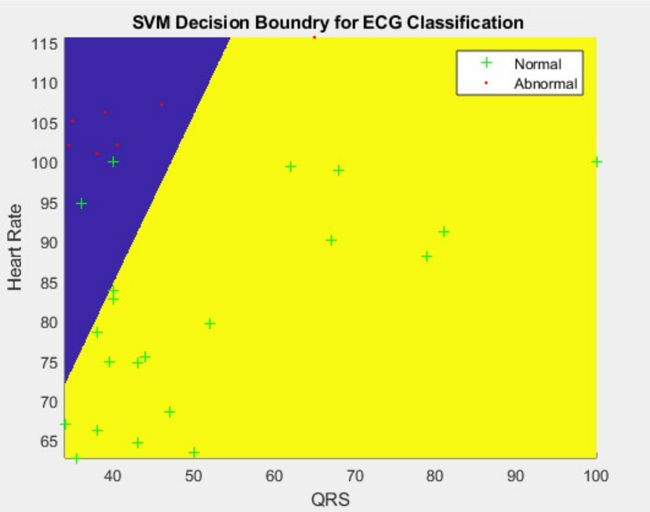


Fig. 6: ECG classification using SVM

TABLE III: The accuracy of machine learning algorithms.

Machine learning method	Accuracy
Decision Tree	83.3%
K-Nearest Neighbours	86.7%
Linear Discriminant	90.0%
Support Vector Machine	96.7%

for our scenario. The accuracy of SVM was very high 96.7% in a short time training as shown in table III.

A full SVM algorithm is implemented in Matlab for our model. After the feature extraction step, the values of features for the 48 patients are stored in the local database. The data then is divided into two sets: the first set is for training and used 80% of data while the second set contains 20% of data for testing. Two features are selected QRS and heart rate. Those features are fed into the algorithm to find the decision boundary between normal and abnormal classes.

The implemented SVM was able to classify the signals and draw a hyperplane between normal and abnormal cases as shown in Fig. 6. The green plus sign and the red dots represent the normal and abnormal data respectively. The hyperplane in the figure was able to differentiate between normal and abnormal classes using yellow and blue colours respectively. The data was fitted correctly between the classes. The accuracy was 90% which is high in comparison with previous research in [5]. The comparison is accomplished using SVM algorithm on MIT-BIH database and with the same features. The classification accuracy is calculated by computing the true positive (TP), false positive (FP), true negative (TN) and false negative (FN) as expressed by eq. 3.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (3)$$

IV. Conclusion

Various IoT homecare management system are available for providing comfort living. In this paper, we focused on one of the healthcare model for ECG monitoring. On this model signal enhancement, feature extraction and classification are provided. The classification applied in two ways; fixed threshold values and machine learning. Machine learning algorithm was applied as a solution of the accuracy limitation. To this end, we conclude that classifying data using machine learning will help in increasing the accuracy of homecare management systems. Moreover, our experiment results show that our model is more accurate than other researches in the diagnosis purpose of heart diseases. Future work will involve testing the proposed algorithm on huge and new database, and applying deep learning algorithms to find higher classification accuracy.

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